Dynamic optimization of water temperature for maximizing leaf water content of tomato in hydroponics using an intelligent control technique

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Abstract

In this study, the dynamic optimization of water temperature, which maximizes the leaf water content of tomatoes in hydroponics, was conducted using neural networks and genetic algorithms. The leaf water content was estimated from leaf thickness in a continuous and non-destructive manner using an eddy current-type displacement sensor. Identification of model mechanisms was achieved and a dynamic model was built using neural networks. A three-layered neural network allowed such a complex system to be successfully identified and generated the model. Next, the control process was divided into six steps and the optimal six-step set points for water temperature that maximizes the leaf water content were examined by simulating the identified neural-network model, using genetic algorithms. The length of the control process was 10 hours, and each step took 90 minutes. The optimal 6-step set points for the water temperature were 40→10→40→10→40→38°C, under the constraint of a fixed water temperature from 10 to 40°C. From simulation, it was confirmed that this operation is effective in maximizing the leaf water content of the tomato. Finally, this operation was applied to a real system. The resulting leaf water content in this operation was about 1.15 times larger than that in a conventional control. It is suggested that this control technique is useful for promoting water uptake of the root and associated higher leaf water content during a short-term period within a day.

Keywords: tomato plants, neural network, genetic algorithm, water uptake, eddy current-type displacement sensor

INTRODUCTION

Hydroponic cultivation allows more accurate and flexible control of environmental factors in the root zone than soil cultivation (Zeroni et al., 1983). The promotion and high-quality production of plants can also be expected from optimal control of the root-zone environment. Ikeda and Osawa (1984) reported that root temperature is an important factor for affecting plant growth directly. Davis and Lingle (1961) elicited increased growth with warmed roots (25-30°C) and decreased growth when roots were cooled below ambient, i.e. below 15°C (Martin and Wilcox, 1963). It is, however, difficult to measure the dynamic change in the leaf water content of the intact whole plant directly and continuously, without damaging the plant. Leaf thickness is used as a sensitive indicator for estimating leaf water content of the plant. As such, Búrquez (1987) and Meidner (1990) have used indirect methods for monitoring water status based on the use of displacement transducers to measure swelling and shrinkage in a wide range of plant tissues such as in the leaf. In this study, therefore, the leaf water content was estimated from leaf thickness. An eddy current-type displacement sensor allows the leaf thickness to be measured in a continuous and non-destructive manner.

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The optimal control strategy is determined by predicting the future behaviour of the process using a dynamic model. In general, however, it is difficult to construct such a dynamic model successfully, requiring complex physiological processes on relationships between leaf water content and water temperature while using conventional mathematical approaches characterized by deterministic parameters and mathematical equations. Identification methods present a new, rapid modelling approach to simulate the behaviour of plant production systems (Morimoto et al., 1996, 2006; Morimoto and Hashimoto, 2000; Morimoto, 2007). It is possible to adapt to the time-variation of the physiological status of the plant if such an identification procedure is repeated periodically during the growing process of the plant.

Intelligent approaches, such as neural networks, are effective in building dynamic models of complex systems because they can acquire the essential dynamics using their high learning capability (Rumelhart et al., 1986). In plant production systems, artificial neural networks (ANN) have been widely applied to identify physiological responses of plants (Morimoto et al., 1996, 2006; Morimoto and Hashimoto, 2000; Morimoto, 2007; Yumeina and Morimoto, 2014).

The objective of this study was to identify the temporal dynamics of leaf water content by measuring the leaf thickness of tomato plants. In our previous research, it was found that the leaf water content was affected by water temperature. This study aimed to find the optimal 6-step set points of water temperature that maximize the leaf water content of tomato. Simulation of the identified model was done using an intelligent control technique combined with neural networks and genetic algorithms. The manipulating factor was water temperature and the controlled factor was the leaf water content of tomato plants grown in hydroponics.

MATERIALS AND METHODS

Plant material and measuring systems

The experiment was conducted in a growth chamber of Ehime University from October to December 2014. Plant materials used in this experiment were tomato plants (*Solanum lycopersicum* L. 'Momotaro'). Plants were grown using standard nutrient solution with an electrical conductivity (EC) set at 1.2 dS m^{-1}. At 14 days after transplanting or when plant height reached 20-30 cm, plants were moved to a hydroponic system situated in a climate chamber (LHU-112M, Tabai-Espec), where the air temperature and relative humidity were strictly controlled at an accuracy of ±0.1°C and ±3% RH, respectively. Light source was LED light, producing 646 mol PAR. The water temperature of the nutrient solution in hydroponics was controlled using a heater and cooler.

Leaf thickness measurement for estimating leaf water content

In this study, leaf water content was estimated from leaf thickness. The leaf thickness was measured in a continuous and non-destructive manner using an eddy current-type displacement sensor (ECS) (PU-05 model AEC-5505). An aluminium plate (10×10×1 mm) was put on the leaf in order to generate an electromagnetic field. A high-frequency current was supplied to the coil inside the sensor head to generate a high-frequency electromagnetic field, and an ECS was generated on the surface of the target and the sensor coil impedance is changed. The sensor system detects the resulting change in oscillation strength to identify the relationship between displacement and voltage.

Dynamic optimization problem

The optimal control problem in this study was to maximize leaf water content of tomatoes during the light period by controlling water temperature. The control length was a short term, within 10 hours.

Let LT(k) (k=1, 2, …, N) be a time series of leaf thickness of the plant, as affected by water temperature WT(k) at time k. An objective function, F(WT), was given by the integration of leaf thickness during the final control step (6-step, $N_5 \leq k \leq N$):

$$F(WT) = \sum_{k=N_5}^{N} LT(k) \quad (1)$$

The length of the whole control process was N=10 hours. To realize dynamic optimization, the control process was divided into six steps. The length of each step was 90 minutes. Therefore, the dynamic optimization problem was to determine the 6-step set points of water temperature that maximize the objective function F(WT). That is, an optimal value was given by the optimal combination of the 6-step set points for water temperature. For the constraint of water temperature (WT), we used 10°C for the minimum value and 40°C for the maximum value.

Optimal control system for dynamic optimization of hydroponic cultivation

Figure 1 shows a block diagram of an optimal control system for realizing dynamic optimization of plant growth in hydroponics. It consists of a feedback control system to control the root-zone environment and a decision system to determine the optimal set point of the root-zone environment. The manipulating factor for control is the root-zone environment and the optimal set points are determined using a decision system based on physiological responses of the plant and root-zone environment measured by sensors.

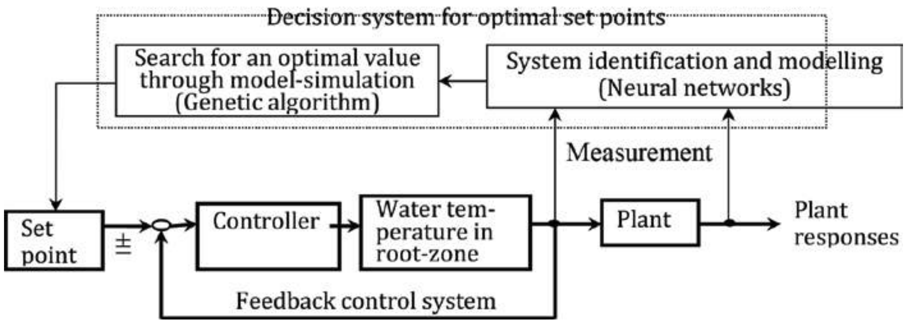

Figure 1. Block diagram of a speaking plant-based optimal control system for hydroponic cultivation.

The decision system consists of neural networks and genetic algorithms, and is used to determine the optimal set points of water temperature during the initial growth (seedling) stage. In this method, plant responses, affected by environmental factors in the root-zone, were first identified using neural networks, and then the optimal environment set-points were determined through simulating the identified neural-network model using genetic algorithms. If these two procedures, identifying plant responses and determining an optimal value, were repeated periodically during the cultivation period to adapt to the time-variation of the physiological status of the plant, then both optimization and adaptation can be satisfied.

1. Neural network application for dynamic identification.

In this study, a one-input (water temperature) and one-output (leaf water content) model was built. Figure 2a shows the block diagram of a one input-one output system. Figure 2b shows a three-layer neural network with time-delay operator for identifying and modelling this system. The current output LWC(k) was estimated from historical input data {WT(k),…,WT(k-n)} and from past historical output data [LWC(k-1), …, LWC(k-n)]. The learning method was error back-propagation (Rumelhart et al., 1986). Where *n* is the system order (number of system parameters), the unknown function *f*(.) can be approximated by a neural network:

$$LWC(k) = f(LWC(k-1), \ldots, LWC(k-n), WT(k), \ldots, WT(k-n)) \quad (2)$$

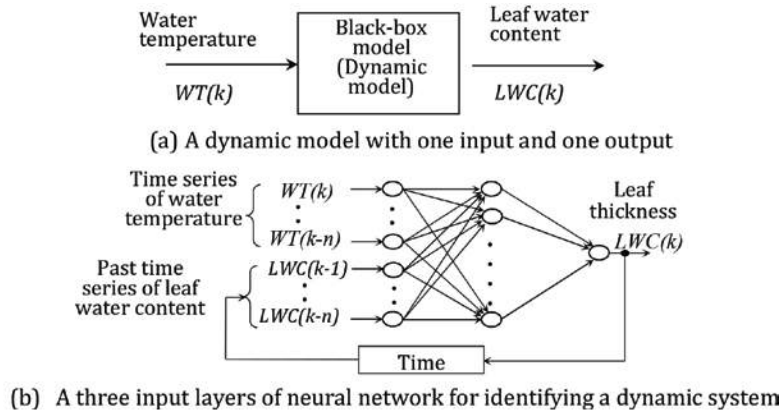

Figure 2. Block diagram of a dynamic model with one input (water temperature) and one output (leaf water content) and a time-delay neural network for identifying a dynamic model.

2. Genetic algorithm application for searching an optimal value.

Figure 3 shows a diagrammatical view of this simulation method. The total number of combinations of the 6-step set points of water temperature under the constraint of 10 to 40°C was 31^6 sets using increments of 1°C between 10 and 40°C in each step. Therefore, the numerous output responses of leaf water content were obtained through simulation.

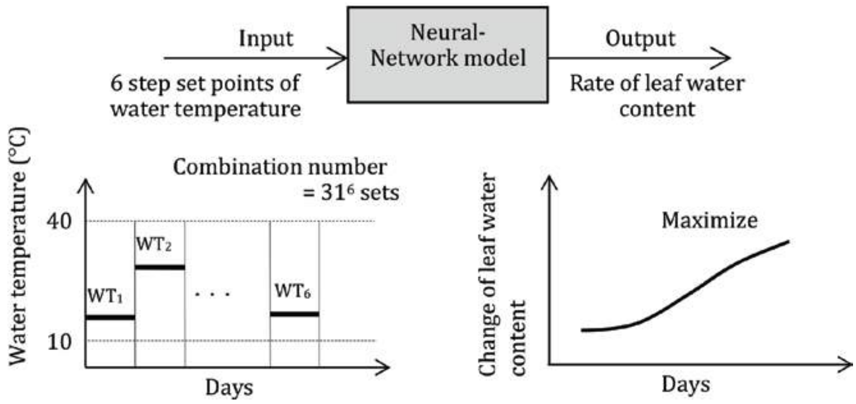

Figure 3. Method for finding an optimal value (combination of the 6-step set points) of water temperature that maximizes the rate of leaf water content (objective function) through simulation.

A flow chart showing the searching process for determining the optimal value using genetic algorithms is shown in Figure 4. The procedure is as follows. Step 1: an initial population consisting of several individuals is generated at random. Step 2: new individuals in another population are added to the original population to maintain diversity. Step 3: crossover and mutation operations are applied to the individuals selected at random. Step 4: the fitness values of all individuals are calculated using the neural-network model and their performances are evaluated. Step 5: superior individuals are selected and retained for the next generation (selection). Step 6: steps 2 to 5 are repeated until an arbitrary condition is satisfied. An optimal value is given as an individual with highest fitness. An elitist strategy was used for selection.

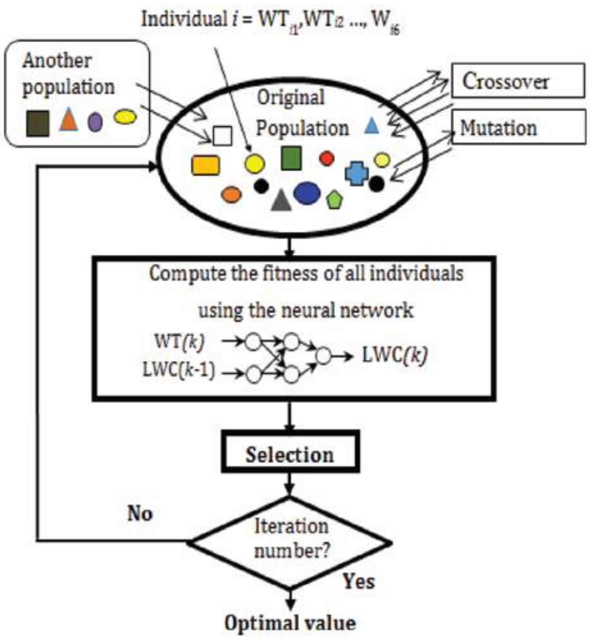

Figure 4. Flow chart of the searching process for determining the optimal value using genetic algorithms.

RESULTS AND DISCUSSION

Relationship between leaf thickness and leaf water content

The relationship between water content and weight of the tomato leaf was determined from the correlation between observed leaf water content and leaf weight, and the correlation between leaf weight and leaf thickness was next calculated. Data on the relationship between leaf water content and leaf weight showed a very good correlation (r^2=0.9477).

Various types of dynamic responses of leaf thickness to water temperature for model identification

Next, data for identification were obtained to make a dynamic model. Figure 5 shows four typical types of dynamic response of the leaf thickness, and therefore leaf water content, of the tomato to changes in water temperature over 9 h. The water content increased in proportion to the water temperature. However, an excessively high water temperature of more than 60°C reduced the leaf water content. For identification, eight patterns of the input and one pattern of the output were obtained for learning and validation of the neural-network model, and a black-box model for predicting the leaf water content of the plant was created.

Identification results

Comparison of the estimated and observed responses of the leaf thickness to water temperature showed that the identification result using a neural network was close to the observed one. Figure 6 shows the estimated step responses of leaf thickness as affected by the step inputs of water temperature. The step response became larger in the first half of the response as the step input of the water temperature became higher. At higher water temperatures of more than 40°C, however, significant decreases in the leaf thickness were observed in the latter half of the response.

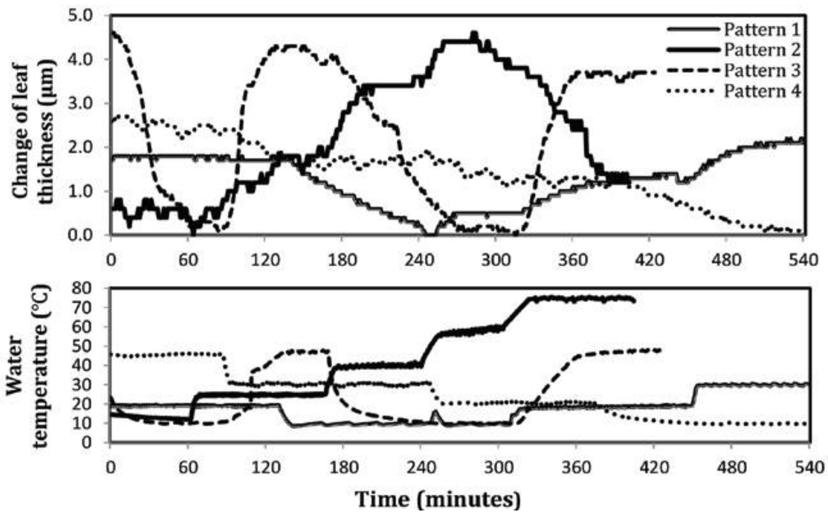

Figure 5. Four typical types of dynamic change in the leaf thickness of the tomato grown in hydroponics, as well as water temperature, used for identification.

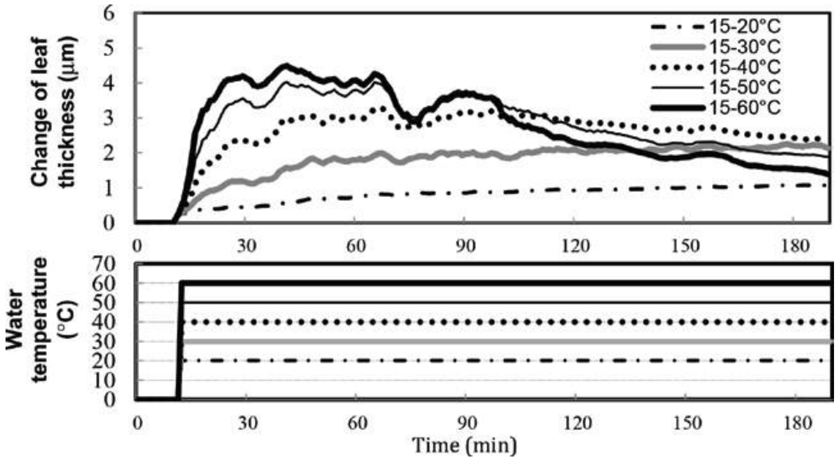

Figure 6. Step responses of leaf thickness as affected by the step inputs of water temperature from 15 to 20, 30, 40, 50 and 60°C, obtained by simulation.

Figure 7 shows the estimated and observed static relationships between water temperature and leaf thickness of the tomato in more detail. The estimated values in Figure 7a were those obtained at 170 min after the step input of water temperature in Figure 6. The leaf thickness increased until the water temperature reached about 35°C. Above 35°C, however, leaf thickness decreased with increasing water temperature. Leaf thickness, including root water uptake of the tomato, was significantly suppressed by high water temperature. We found that the relationship between water temperature and leaf thickness is well described by a mountain-shaped curve with an optimum value of about 35°C. It is noted that this result was obtained from the response in steady state and short-term, i.e., within several hours. These results suggest that a reliable computational model (neural-network model) could be obtained to predict the behaviour of leaf thickness under any combination of the 6-step set points of water temperature.

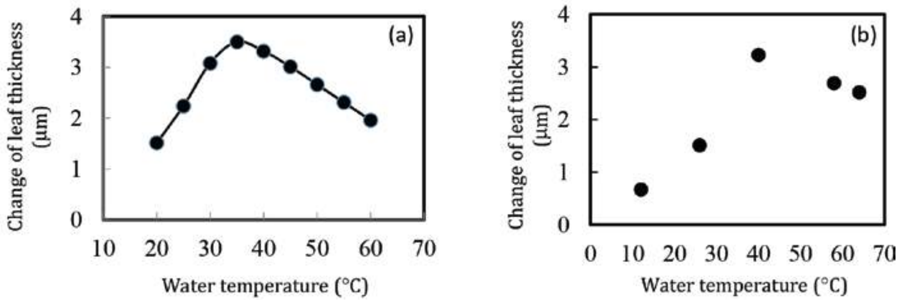

Figure 7. Static relationship between water temperature and leaf thickness. (a) Estimated relationship. (b) Observed relationship.

Optimal control results

Figure 8 shows the estimated optimal control performances of leaf thickness under different constraints of water temperature (manipulating variable), calculated from the model simulation. Lines A, B, C were cases where the constraints of water temperature took from 10 to 50, 10 to 40 and 10 to 30°C, respectively. One step of the control process was 90 minutes. Thus, under the constraint of the step of water temperature of 10 to 40°C or 10 to 50°C, an intelligent optimization technique recommended to repeat an operation that increases the water temperature to the maximum value and then drops it to the minimum value is more effective than keeping it constant at a suitable temperature (30°C) in order to increase the leaf thickness and thus leaf water content of the tomato. These results suggest that an operation raising the water temperature to the maximum level and then dropping it to the minimum level promotes root water uptake and then maximizes the leaf water content of the tomato.

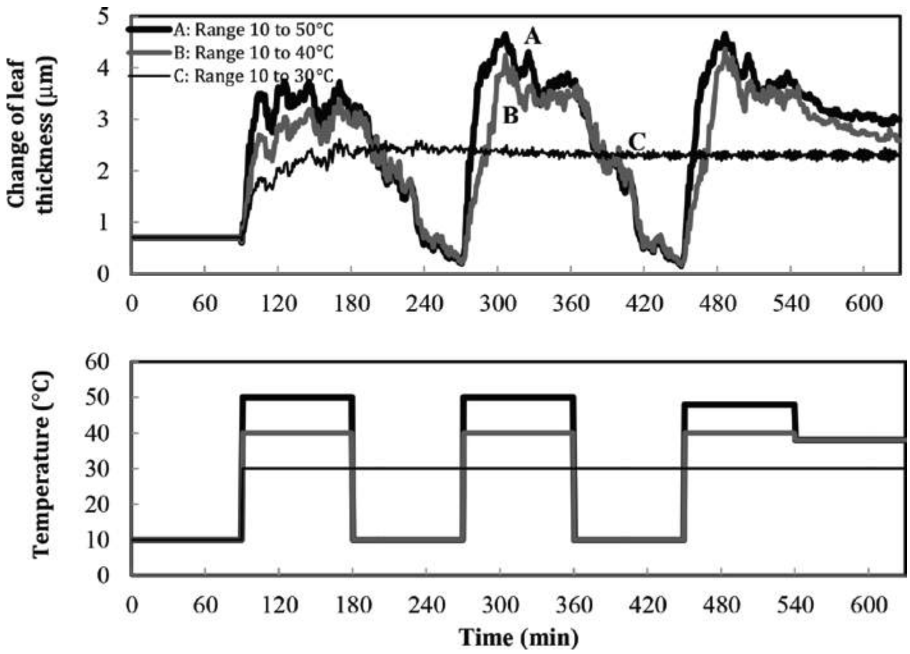

Figure 8. Estimated optimal control performances of water temperatures that maximize the leaf thickness of the tomato under different constraints (A, B and C) of water temperature (WT). A, 10≤WT≤50°C; B, 10≤WT≤40°C; C, 10≤WT≤30°C.

This optimal temperature might be a little higher than the commonly used optimal temperature (25-30°C), while this is the result of the short-term response. However, Yoshida and Eguchi (1994) showed that root water uptake increased with water temperature up to

33°C in a response period of several hours. The increase in leaf water content with water temperature can be explained because the thermal motion of water molecules becomes higher and water viscosity decreases with increasing water temperature (Falah et al., 2010). However, excessively high water temperatures above 35°C induce physiological disorders in the root system and result in poorer root water uptake and leaf water content. This is because high water temperature causes lower dissolved oxygen in the hydroponic solution and then depresses root activity. Consequently, uptake of water and various types of nutrient ions by roots are inhibited. It is assumed that, in the short-term, leaf water content as a result of higher water uptake by roots increases with the water temperature up to approximately 35°C and is depressed at higher water temperatures (Hurewitz and Janes, 1983; Falah et al., 2010). However, long-term application of such high temperatures will bring about poorer growth of the plant. This means that the optimal water temperature for short-term dynamic control is different from that for long-term management.

Considering the dynamic characteristics of leaf water content to water temperature obtained from dynamic optimization including model simulation, the optimal value that maximizes the leaf water content was not a constant value, but was given by a combination of duration of maximum value (40°C) and minimum value (10°C) when the constraint of the water temperature was a set point of either 10 to 40°C; the combination of the sudden rise and drop of the water temperature between 10 to 40°C had a tendency to increase the leaf water content of the plant compared with when the water temperature was maintained at a suitable level (30°C) throughout the control process.

In general, two temperatures, 40 and 10°C, are excessively high and low for the physiological ecological activities of the plant. It can be seen that such a significant rise and drop in water temperature during the control process resembles a kind of stress application for the plant and seems to be unsuitable for plant growth. We surmise that the physiological activities of the plant became active after removing the temperature stress, while it decreased when applying temperature stress to the plant. This means that applying temperature stress to the plant optimally accelerated physiological responses and promoted root water uptake (Wahid et al., 2007; Huang et al., 2012). The reason is that, by applying a suitable heat stress, the plant acquired a transient thermal tolerance and promoted root water uptake even at a higher water temperature. Many researchers have supported the idea that application of a suitable heat stress to the plant is effective in reducing loss of quality by the plant (Lurie and Klein, 1991; Sabehat et al., 1996; Lurie, 1998). Moreover, in our experiment on the storage process of fruits, water loss from fruits could be successfully inhibited by applying heat stress (40°C) to the fruit (Morimoto and Hashimoto, 2003). It is therefore suggested that a suitable (or optimal) application of such environmental stresses as heat stress to the plant is effective in promoting root water uptake and then increase in leaf water content of plants, requiring short-term management of the water temperature in hydroponics (Morimoto, 2007; Oh et al., 2009; Yumeina and Morimoto, 2014).

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